# An Optimization Framework for Driver Feedback Systems

Andreas A. Malikopoulos, *Member, IEEE*, and Juan P. Aguilar

***Abstract*—Modern vehicles have sophisticated electronic control units that can control engine operation with discretion to balance fuel economy, emissions, and power. These control units are designed for specific driving conditions (e.g., different speed profiles for highway and city driving). However, individual driving styles are different and rarely match the specific driving conditions for which the units were designed. In the research reported here, we investigate driving-style factors that have a major impact on fuel economy and construct an optimization framework to optimize individual driving styles with respect to these driving factors. In this context, we construct a set of polynomial metamodels to reflect the responses produced in fuel economy by changing the driving factors. Then, we compare the optimized driving styles to the original driving styles and evaluate the effectiveness of the optimization framework. Finally, we use this proposed framework to develop a real-time feedback system, including visual instructions, to enable drivers to alter their driving styles in response to actual driving conditions to improve fuel efficiency.**

***Index Terms*—Driver information systems, fuel economy, optimization methods, transportation, vehicle driving.**

## I. Introduction

INCREASING demand for improved fuel economy and reduced emissions without sacrificing performance has led to significant research and investment in advanced internal combustion engine technologies. These technologies, such as fuel injection systems, variable geometry turbocharging, variable valve actuation, and exhaust gas recirculation, have introduced a number of engine variables that can be controlled to optimize engine operation. Computing the optimal values of these variables, which is referred to as engine calibration, has been shown to be particularly critical for achieving high engine performance and fuel economy while meeting emission standards. Consequently, engine calibration is defined as a procedure that optimizes one or more engine performance criteria (e.g., fuel economy, emissions, and power) with respect to the engine variables. State-of-the-art engine calibration methods generate a static correlation between the values of the engine variables and the corresponding operating points for specific driving cycles (e.g., steady-state engine operating points corresponding to the vehicle's speed profiles for highway and city driving). This correlation is incorporated into the electronic control unit (ECU) of the engine that controls engine operation. While the engine is running, these correlations are interpolated to provide values of the engine variables for each operating point. However, each individual driving style is different (e.g., speeding, rapid acceleration, and braking) and rarely meets those driving conditions and testing for which engine calibration has been derived. As a consequence, consumers often complain that their new cars do not achieve the gas mileage estimates displayed on the window stickers. In recent research, the theoretical framework and algorithms [1] were developed to make the engine of a vehicle an *autonomous intelligent system* capable of learning its optimal calibration in real time while the driver is driving the vehicle. Through this new approach, the engine progressively perceives the driver's driving style and eventually learns to operate in a manner that optimizes fuel economy and emissions for that style. This technology could eventually improve fuel economy and emissions in new vehicles. However, developing a means for optimizing driver behavior could yield substantial fuel economy improvements in existing fleets.

Recent studies indicate that fuel consumption and emissions can be reduced in existing vehicles by as much as 30% by altering the driver's driving style [2], [3]. One of the most promising approaches involves providing immediate information to the driver about the effect of driving behavior on fuel consumption. Riener [4] discussed a method to support eco-driving by applying subliminal persuasion to change a driver's steering behavior. Kamal *et al.* [5] presented an ecological driving system for running a vehicle on roads with various slope variations. Takeda *et al.* [6] proposed a self-coaching system to improve driving behavior by allowing drivers to review a record of their own driving activity. Dam [7] conducted a survey about the perception of achievable automobile fuel economy, indicating that significant fuel economy enhancement can be achieved with a few driving adjustments. A significant research effort has focused on investigating the impact of driving behavior on fuel consumption. Van Mierlo *et al.* [8] studied how driving styles and traffic measures can affect fuel consumption and vehicle emissions. The study evaluated driver behavior and fuel economy over specific driving routes, before

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and after supplying the drivers with tips on fuel-efficient driving practices, to determine whether a change in driver behavior had an impact on fuel economy. Ericsson [9] focused on independent factors to describe driving patterns and behaviors and to investigate their effects on fuel consumption. Hooker [10] conducted a study aimed at generating reliable advice concerning optimal driving styles to maximize fuel economy. Ross [11] investigated the factors that affect fuel economy of light vehicles and can be used to estimate the effect of driving styles and vehicle characteristics. Ahn *et al.* [12] introduced a method for estimating fuel consumption based on driver-related factors such as instantaneous speed and acceleration.

Hybridization of conventional powertrain systems reduces the impact of driving styles on fuel economy because the power management controller decouples the driver and the engine. Manzie *et al.* [13] examined the possible fuel economy benefits that can be achieved with emerging technologies such as hybrid electric vehicles and *intelligent* vehicles that use telematics. The latter allow the vehicles to communicate with the road infrastructure and other vehicles to obtain information about the environment. Langari and Jong-Seob [14] proposed an intelligent energy management system for parallel hybrid vehicles that incorporates driving-style identification. Kwon *et al.* [15] investigated the impact of driving cycles on fuel consumption in plug-in hybrid electric vehicles (PHEVs) and concluded that sizing the components of a PHEV according to the most aggressive driving cycle could address their impact on fuel economy. Dardanelli *et al.* [16] proposed a hierarchical control architecture capable of regulating the battery state of charge using a smart phone as an interface between the driver and the vehicle.

A significant number of online resources with tips for improving fuel economy are available to consumers [17]–[19]. These resources provide useful and practical driving tips, such as 1) shifting gears as early as possible (at low engine speed) for cars with manual transmissions; 2) avoiding speeding as drag resistance, and thus fuel consumption, increases with speed; 3) accelerating evenly and smoothly; 4) accelerating less when going up hills and allowing the vehicle to slow down; 5) keeping the vehicle rolling in stop-and-go traffic and avoiding intense acceleration, deceleration, and stopping; and 6) maintaining a constant velocity (e.g., using cruise control, except on very hilly terrain).

Although previous research reported in the literature has aimed at enhancing our understanding of the impact of various driving factors on fuel economy, no research has reported explicitly formulating the relation between them. Such a formulation could be used to develop a competent interface to "translate" the optimal driving behavior into simple visual instructions. This paper and related research of the authors [20] have two main objectives: 1) to report on those driving factors that have a major impact on fuel economy of vehicles and explicitly quantify their impact and 2) to develop an optimization framework that can be used to optimize a driving style with respect to these driving factors through a driver feedback system.

The contributions of this paper are 1) the identification and justification of key driving factors that can provide an efficient indication of transient engine operation deemed characteristic of high fuel consumption, 2) the construction of a set of polynomial metamodels that explicitly formulates the relationship between fuel consumption and the identified driving factors, 3) the formulation of an optimization problem that can be used to optimize a driving style based on the driver's needs and preferences, and 4) the development of a driver feedback system that can provide visual instructions to the driver to alter his/her driving behavior.

The remainder of this paper proceeds as follows: In Section II, we develop the general framework for identifying two key driving factors. In Section III, we formulate a constrained optimization problem with respect to these driving factors. In Section IV, we evaluate the efficiency and effectiveness of the optimization framework in terms of fuel economy benefits, and we develop a competent visual interface that translates the results of the optimization problem into simple visual instructions. In Section V, we present our conclusions.

## II. Driving Factors

### A. Engine Operation and Fuel Consumption

Engines are streamlined syntheses of complex physical processes that determine a convoluted dynamic system. They are operated with reference to engine operating points, that is, the pair of engine torque and speed, and the values of various engine controllable variables. At each operating point, these values highly influence various engine performance criteria (e.g., fuel economy, emissions, and power). This influence becomes more important at engine operating point transitions designated by the driver's driving style. To evaluate the impact of a driving style on fuel economy through simulation, standard dynamometer driving schedules (DDSs, or simply driving cycles) were used [i.e., vehicle speed profiles established by the U.S. Environmental Protection Agency (EPA) for testing and measuring fuel economy and emissions]. These driving cycles are representative of typical urban and highway commutes. They essentially represent a situation in which the driver desires a particular vehicle's speed profile deemed characteristic of his/her driving style. The implicit assumption here is that if the key driving factors can be used to relate the fuel economy variations among different driving cycles, then it should also be possible to use these same factors to reflect the impact of different driving styles.

Transient operation constitutes the largest segment of engine operation over a driving cycle compared with the steady-state engine operation [21]. Fuel consumption and emissions during transient operation are extremely complicated, significantly vary with each particular driving cycle, and are highly dependent upon engine calibration [22]. State-of-the-art engine calibration methods generate a static correlation between the values of the engine variables and the corresponding steady-state operating points. This correlation is incorporated into the ECU of the engine to control engine operation. While the engine is running, these correlations are being interpolated to provide values of engine variables for each operating point.

To overcome the limitations imposed by the engine calibration schemes, it is always preferable to operate the engine over steady-state operating points (e.g., highway driving) that are well optimized through engine calibration and avoid transient

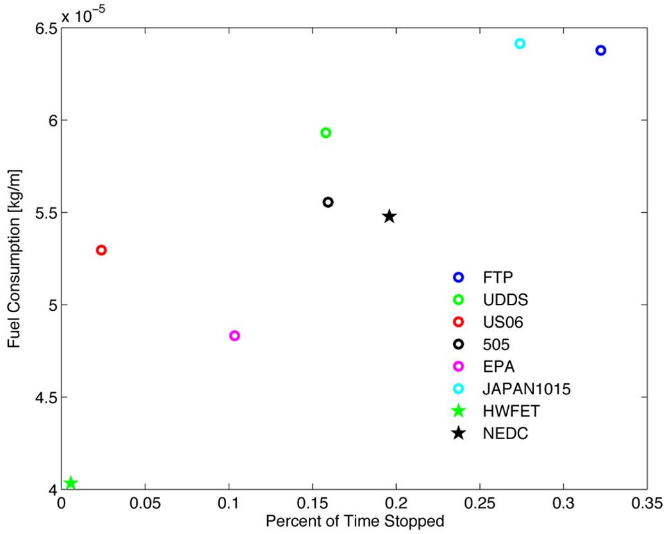


Fig. 1. Fuel consumption versus the percentage of time the vehicle is stopped for various EPA driving cycles.

operation (e.g., stop-and-go driving and rapid acceleration). Furthermore, eliminating near-idle engine operation directly enhances fuel economy because at idle, the efficiency is zero because no usable work is being drawn from the engine. Consequently, two factors have a major impact on engine operation and, thus, on fuel economy. These are 1) the *stop factor* and 2) the *coefficient of power demand*.

### B. Stop Factor and Coefficient of Power Demand

The *stop factor* is defined as the amount of time during a driving cycle that the vehicle is stopped (i.e., the time that the vehicle's velocity is zero divided by the total duration of the driving cycle). This factor provides a convenient indication of idle engine operation over a driving cycle. When a vehicle is stopped during a drive cycle, the engine is idling. In this situation, fuel is consumed but the distance traveled is zero; hence, the fuel economy is reduced to 0 mi/gal.

To understand the impact of the stop factor on fuel consumption, it is useful to consider the fuel consumption per meter for several driving cycles, as shown in Fig. 1.

The resulting plot indicates that there is a monotonic increasing correlation between the stop factor and fuel consumption: As the stop factor or engine idling increases, fuel consumption also increases. The Highway Fuel Economy Test (HWFET) driving cycle developed by the EPA, for example, is a representation of highway driving under 60 mi/h for testing and measuring fuel economy and emissions and contains the least amount of time stopped. This cycle shows the lowest amount of fuel consumption per meter. The Japan 10-15 and Federal Test Procedure (FTP) cycles, which constitute a representation of city driving, have the highest percentage of time stopped compared with other cycles and, as a result, demonstrate higher fuel consumption per meter.

### C. Coefficient of Power Demand

The second driving factor considered here is the *coefficient of power demand*. It provides an indication of the transient engine operation since it is proportional to power demanded

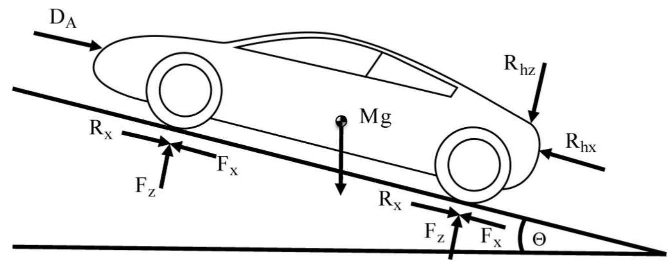


Fig. 2. Forces acting on a vehicle.

by the driver. This power is the work done by the vehicle over time, which is equal to the total force, i.e., $F_{\text{total}}$, acting on the vehicle multiplied by the distance traveled, i.e., $d$. Thus

$$P = \frac{W}{t} = F_{\text{total}} \cdot \frac{d}{t}. \tag{1}$$

The forces acting on the vehicle in the longitudinal direction are shown in the free-body diagram of a vehicle in Fig. 2. These forces consist of 1) tractive force ($F_x$), 2) drawbar force ($R_{hx}$), 3) aerodynamic force ($D_A$), 4) rolling resistance force ($R_x$), and 5) the component of vehicle weight in this direction. Total force $F_{\text{total}}$ is equal to the inertial force, i.e.,

$$M \cdot \alpha = F_{\text{total}} = F_x + R_{hx} - D_A - R_x - M \cdot g \cdot \sin\theta \tag{2}$$

where $M$ is the vehicle mass, $\alpha$ is the vehicle acceleration in the longitudinal direction, and $g$ is the gravitational constant. Substituting (2) in (1), we have

$$P = M \cdot \alpha \cdot \frac{d}{t} = M \cdot (\alpha \cdot v) \tag{3}$$

where $v$ is vehicle speed. Consequently, the power demanded by the driver is proportional to the product of vehicle speed $v$ and acceleration $\alpha$. This product is defined as the *coefficient of power demand*.

Fig. 3 shows the variation in fuel consumption per meter for several driving cycles with respect to the average speed of each driving cycle. The resulting trend indicates that those driving cycles with lower average speed tend to have higher fuel consumption per meter, which might be associated with frequent transient engine operation. HWFET exhibits the lowest fuel consumption as it represents highway driving conditions and, thus, steady-state engine operation at high average vehicle speed. The Japan 10-15 and FTP driving cycles exhibit the highest fuel consumption per meter, which is characteristic of their low average speeds. Thus, these three driving cycles were used to further investigate the impact of the coefficient of power demand on fuel consumption.

In this context, the impact of the coefficient of power demand on fuel consumption was normalized and compared with the normalized fuel consumption rate over a given driving cycle. The normalization in both cases was with respect to their maximum values. It appears that there is a monotonic correlation between the coefficient of power demand and fuel consumption. This correlation is shown in Fig. 4 for the FTP and HWFET driving cycles combined. To further investigate this relationship, the parts of this combined driving cycle that correspond to a high fuel consumption rate were identified.

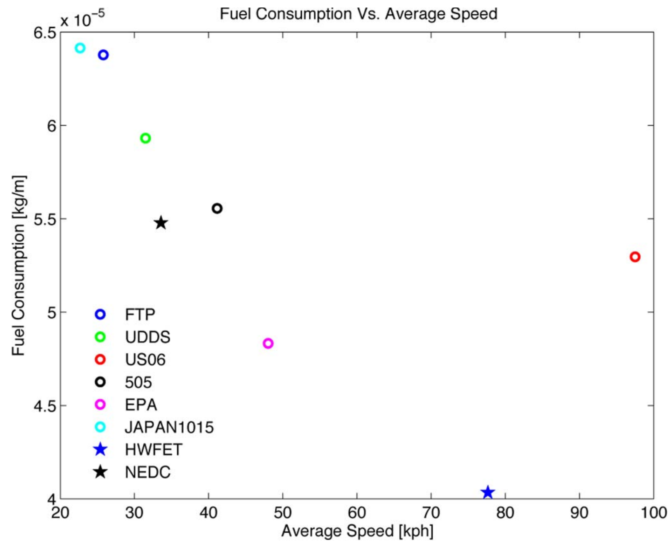


Fig. 3. Fuel consumption versus average speed for various driving cycles.

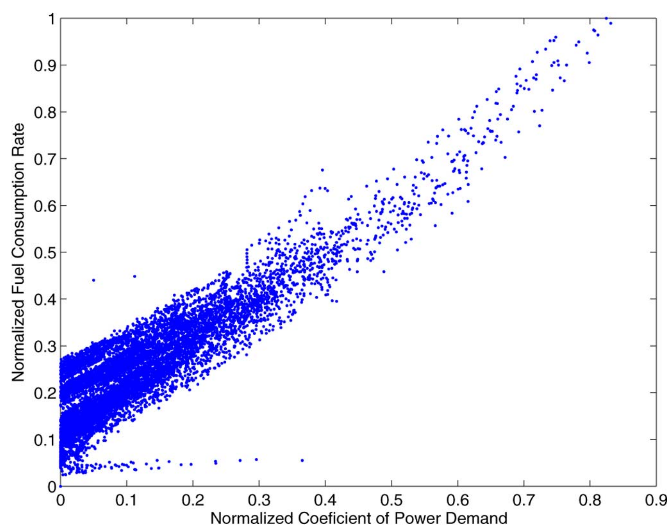


Fig. 4. Normalized fuel consumption rate with respect to the coefficient of power demand for the FTP and HWFET driving cycles combined.

*High fuel consumption rate* is defined to be the values of the fuel consumption rate that are equal to or greater than the high fuel point, specified as two standard deviations above the mean fuel consumption rate. These high fuel consumption points were then mapped onto the graph of the driving cycle (in red) where they occurred. Then, the values of the coefficient of power demand, which are equal to or greater than the high fuel points, were also plotted (in green) along the driving cycle, as shown in Fig. 5. Apparently, both the coefficient of power demand and the high fuel consumption rate provide the same information; thus, the coefficient of power demand constitutes a suitable indicator for aspects of a driving cycle that have a strong influence on fuel consumption. Fig. 6 shows the linear correlation between the normalized coefficient of power demand and fuel consumption for the FTP driving cycle. The plot with values of the coefficient of power demand equal to or greater than the high fuel consumption rate points is shown in Fig. 7. The same qualitative results were observed for the Japan 10-15 and other standard DDSs established by the EPA.

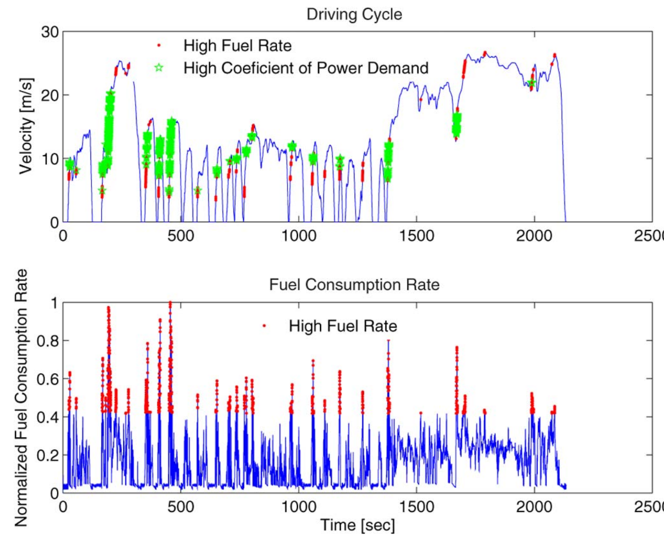


Fig. 5. High fuel consumption rates over the normalized fuel consumption rate for the FTP and HWFET driving cycles combined.

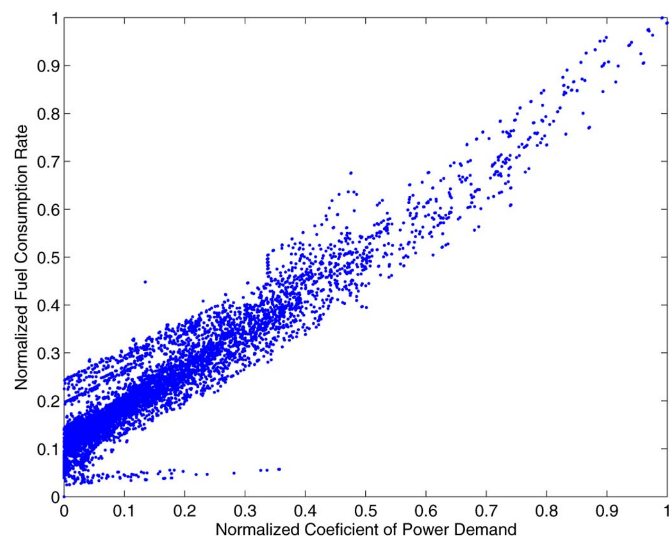


Fig. 6. Normalized fuel consumption rate with respect to the coefficient of power demand for the FTP driving cycle.

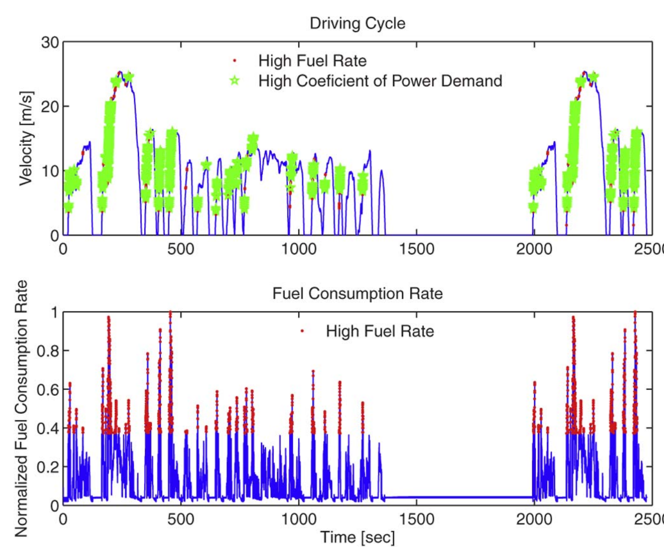


Fig. 7. High fuel rates over the normalized fuel consumption rate for the FTP driving cycle.

Although the conjoint attributes of these two driving factors (the stop factor and the coefficient of power demand) entail a comprehensive intimation of fuel consumption, the stop factor is a commuting characteristic rather than a driving characteristic. As such, it cannot be altered by changing driving behavior but only by modifying the route. Consequently, in the optimization problem formulation discussed here, the goal is to optimize a driving cycle with respect to the coefficient of power demand.

## III. Optimization Framework

To develop the framework to optimize a driving style with respect to the coefficient of power demand, we used Autonomie [23]. Autonomie is a MATLAB/Simulink simulation package for powertrain and vehicle model development developed by the Argonne National Laboratory, Argonne, IL, USA. With a variety of existing forward-looking powertrain and vehicle models, Autonomie can support the evaluation of new technologies for improving fuel economy through virtual design and analysis in a math-based simulation environment. A vehicle model from Autonomie's database representing a midsize passenger vehicle was used in this study.

### A. Polynomial Metamodel for Fuel Consumption

To construct an explicit relation between fuel consumption and the coefficient of power demand and to formulate the optimization problem analytically to significantly reduce computation time, a set of polynomial metamodels was constructed. These models can reflect the responses in fuel consumption produced by changes in the coefficient of power demand. A metamodel is a "model of a model" that is used to approximate a usually expensive analysis or simulation process; metamodeling refers to the techniques and procedures of constructing such a model [24]. In this optimization framework, a set of polynomial metamodels was used to express the objective function in the problem formulation analytically. Fuel economy was evaluated through simulation in Autonomie over a grid of values for vehicle speed and acceleration in a particular driving cycle. Then, multivariate polynomial functions were fit to the data using the least squares method. The least squares method is a fundamental approach to parameter estimation. If the model treats the parameters linearly, then the least squares estimate can be calculated analytically [25]. It was assumed that the model to be identified was in the form

$$\hat{y} = \varphi_1(i) \cdot w_1 + \varphi_2(i) \cdot w_2 + \cdots + \varphi_n(i) \cdot w_n \tag{4}$$

where $i = 1, 2, \ldots, n$; $n \in \aleph$ indexes the number of simulation data points; $\hat{y}$ is the output of the model; $w_1, w_2, \ldots, w_n$ are the parameters of the model to be determined; and $\phi_1, \phi_2, \ldots, \phi_n$ are known functions that may depend on other known variables. The model in (4) can be written in the vector form as follows:

$$\hat{y} = \boldsymbol{\varphi}^T(i) \cdot \mathbf{w}. \tag{5}$$

The simulation data points derived from Autonomie correspond to pairs of the measured and regression variables $\{(y(i), \boldsymbol{\phi}^T(i)), i = 1, 2, \ldots, n, n \in \aleph\}$. The problem is formulated to minimize the following least squares cost function with respect to the parameters of the model $w_1, w_2, \ldots, w_n$. Thus

TABLE I
Polynomial Coefficients of Fuel Consumption Metamodels for Different Driving Cycles

| | Japan 10-15 | Combined FTP and HWFET | FTP |
|---|---|---|---|
| $w_1$ | $0.208\times10^{-6}$ | $0.442\times10^{-6}$ | $0.222\times10^{-6}$ |
| $w_2$ | $40.899\times10^{-6}$ | $-5.670\times10^{-6}$ | $4.332\times10^{-6}$ |
| $w_3$ | $-0.532\times10^{-6}$ | $1.166\times10^{-6}$ | $1.250\times10^{-6}$ |
| $w_4$ | $45.419\times10^{-6}$ | $39.269\times10^{-6}$ | $36.217\times10^{-6}$ |
| $w_5$ | $86.518\times10^{-6}$ | $58.284\times10^{-6}$ | $57.877\times10^{-6}$ |
| $w_6$ | $23.923\times10^{-6}$ | $19.279\times10^{-6}$ | $24.245\times10^{-6}$ |
| $w_7$ | $26.602\times10^{-6}$ | $82.426\times10^{-6}$ | $77.482\times10^{-6}$ |
| $w_8$ | $160.640\times10^{-6}$ | $185.360\times10^{-6}$ | $171.200\times10^{-6}$ |
| $r$ | 0.004 | 0.014 | 0.015 |

$$R(w, n) = \frac{1}{2} \sum_{i=1}^{n} \left[ y(i) - \boldsymbol{\varphi}^T(i) \cdot \mathbf{w} \right]^2. \tag{6}$$

The measured variable $y$ is linear in parameters $w_i$, and the cost function is quadratic. Consequently, the problem permits an analytic solution. Our objective was to derive the vector of the model parameters $w_1, w_2, \ldots, w_n$ that makes the error equal to zero. For the optimization problem formulation, it was necessary to derive a polynomial metamodel of fuel consumption with respect to the coefficient of power demand that would be the objective function. A quadratic function of the form

$$\begin{aligned} f(v, \alpha) = {} & w_1 \cdot v^2 + w_2 \cdot \alpha^2 + w_3 \cdot v^2 \cdot \alpha + w_4 \cdot v \cdot \alpha^2 \\ & + w_5 \cdot v \cdot \alpha + w_6 \cdot v + w_7 \cdot \alpha + w_8 \end{aligned} \tag{7}$$

provides an appropriate fitting to the discrete simulation data points of fuel consumption, i.e., $f(v, \alpha)$, with respect to vehicle speed $v$ and acceleration $\alpha$. We also investigated a higher order polynomial metamodel, but this appeared to "overfit" the data. Likewise, a lower order polynomial was not adequate to accurately estimate fuel consumption.

Different sets of discrete simulation data points consisting of a grid of vehicle speed and acceleration for three driving cycles (Japan 10-15, combined FTP and HWFET, and FTP) were derived by running the vehicle model in Autonomie. These sets were used in (6) to compute the polynomial fitting coefficients, i.e., $\mathbf{w}$. To assess the polynomial fitting with the discrete simulation data points, the following equation was used to evaluate the norm of residuals, which yields an indication of satisfactory curve fitting:

$$r = \left( \sum_{t=1}^{n} \left[ f_{\text{f.c.}}(t) - f\left(v(t), \alpha(t)\right) \right]^2 \right)^{1/2} \tag{8}$$

where $f_{\text{f.c.}}(t)$ is fuel consumption over time derived from Autonomie, $f(v(t), \alpha(t))$ is fuel consumption over time estimated by the polynomial metamodel, and $n$ is the time horizon of the driving cycle. Table I lists the values of the polynomial coefficients of the metamodel of each driving cycle and the norm of residuals. The values of the norm of residuals demonstrate that the curve fits the data well.

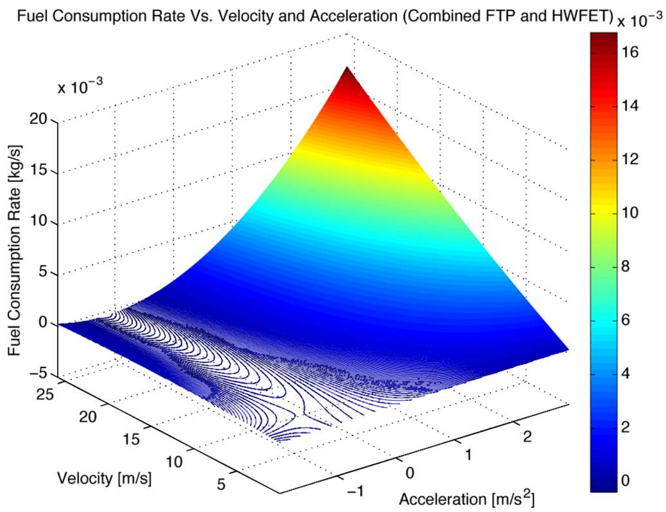


Fig. 8. Fuel consumption metamodel corresponding to combined FTP and HWFET driving cycles.

The fuel consumption estimated by the polynomial metamodel for the combined FTP and HWFET driving cycles is shown in Fig. 8. The response of the metamodels corresponding to the Japan 10-15 and FTP driving cycle were similar both qualitatively and quantitatively to this one.

### B. Optimal Acceleration Profile

This paper poses an optimization framework to determine the optimal values of the coefficient of power demand to improve fuel economy. Consequently, the objective of the optimization problem is to minimize fuel consumption in (7) with respect to vehicle acceleration as the vehicle speed is a dependent variable of the former (i.e., a new acceleration profile will yield a new vehicle speed profile). Deceleration is not generally a major concern because the fuel cutoff controller in modern vehicles can successfully handle rapid deceleration. Although the act of braking consumes kinetic energy that might later be used to reduce fuel consumption during a subsequent acceleration, braking can be considered as part of the traffic rather than a controllable driving characteristic. The rate of deceleration has no impact on fuel economy as the fuel is quickly shut off when braking is applied.

Although a new acceleration profile will yield a new vehicle speed profile, the original driving cycle must somehow be preserved (e.g., stop signs and traffic lights). To avoid the trivial solution (i.e., zero acceleration), a constraint was imposed on the difference between the resulting and the original vehicle speed profile. More specifically, the optimal acceleration profile was constrained to yield a new vehicle speed profile that was no more than 5 km/h less than the original speed profile. However, this hard constraint could significantly reduce the feasible domain of the optimal solution. To overcome this technicality, the constraint was formulated as the norm of the difference between the original and the new speed profiles. This norm should be less than or equal to another norm formulated as the difference between the original and a speed profile that is 5 km/h less than the original. The inherent modularity of the proposed constraint circumvents the hard limit of the derived speed profile to be no more than 5 km/h less than the original speed profile. However, it preserves the average discrepancy to be within these limits, and thus, it enables the feasible space of the acceleration profile to include solutions resulting in smooth shaping of the speed profile. The value of 5 km/h can be altered as desired, thus providing flexibility of having a more or less conservative optimized driving cycle.

Consequently, the following nonlinearly constrained optimization problem was formulated:

$$\begin{aligned} \min_{\alpha} \quad & f\left(v(t), \alpha(t)\right) \\ \text{s.t.} \quad & \|v(t) - v^*(t)\| \le \left\|v(t) - v_{5\ \mathrm{km/h}}(t)\right\| \end{aligned} \tag{9}$$

where $v(t)$ is the original vehicle speed of the driving cycle; $v^*(t)$ is the optimal speed profile corresponding to the optimal acceleration profile, i.e., $\alpha^*(t)$; and $v_{5\ \mathrm{km/h}}(t)$ is the vehicle speed profile, which is 5 km/h less than the original speed profile.

The optimization problem formulation in (9) may yield conservative acceleration profiles with a potentially much longer destination arrival time. To provide more flexibility to the user, a second optimization problem was formulated with a constraint focusing on the arrival time, i.e.,

$$\begin{aligned} \min_{\alpha} \quad & f\left(v(t), \alpha(t)\right) \\ \text{s.t.} \quad & t_{\text{optimized}} \le t_{\text{original}} \cdot (1+q) \end{aligned} \tag{10}$$

where $t_{\text{optimized}}$ is the destination arrival time of the optimized driving cycle, $t_{\text{original}}$ is the destination arrival time of the original driving cycle, and $q$ is the desired percentage that the destination arrival time of the optimized cycle can exceed that of the original driving cycle.

The optimization problems in (9) and (10) were iteratively solved until convergence, using the MATLAB function $fmincon$, based on sequential quadratic programming (SQP) [26]. SQP is one of the most effective methods for nonlinearly constrained optimization. It relies on a profound theoretical foundation and provides powerful algorithmic tools for the solution of large-scale technologically relevant problems. SQP proceeds by computing an approximate solution of a sequence of quadratic programming subproblems in which a quadratic model of the objective function is minimized subject to the linearized constraints.

## IV. Driver Feedback System

### A. Construction of the New Driving Cycle

The acceleration profile, i.e., $\alpha(t)$, yields a vehicle speed profile, i.e., $v(t)$. This speed profile was used to constrain the optimization problem iteratively until convergence to optimal acceleration $\alpha^*(t)$ and speed $v^*(t)$ was achieved. In this iterative process, the construction of the vehicle speed profile needs to preserve the total distance that the vehicle travels and the instances where the vehicle must stop. In other words, the desired route of the driver and the speed limits must be preserved. Integrating the acceleration is not enough to accurately obtain a new driving cycle because some route-related information is not described by the acceleration profile (e.g., when the vehicle is

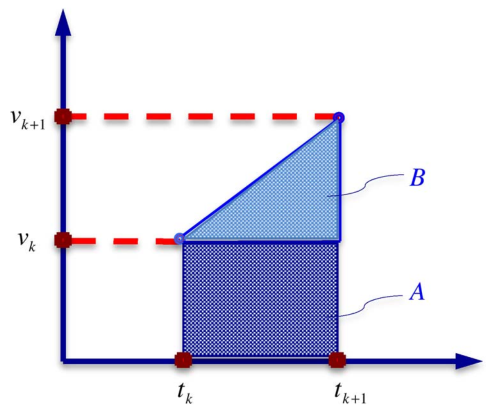


Fig. 9. Vehicle speed construction from the optimized acceleration profile.

stopped and the duration for which the vehicle is stopped). This information is available, however, from the original drive cycle. Therefore, to preserve the total distance, $\Delta s$ should remain constant and can be computed as follows. The distance $\Delta s$ that the vehicle covers within a time interval $\Delta t$ is equal to the sum of the two areas, i.e., $A$ and $B$, shown in Fig. 9.

Hence, the total distance that the vehicle travels is given by

$$\begin{aligned} S &= \sum_{t=1}^{n+1} \Delta s_i = \sum_{k=0}^{n} (s_{k+1} - s_k) \\ &= \sum_{k=0}^{n} \left( v_k \cdot (t_{k+1} - t_k) + \frac{1}{2} \cdot (v_{k+1} - v_k) \cdot (t_{k+1} - t_k) \right). \end{aligned} \tag{11}$$

The time interval, i.e., $\Delta t = t_{k+1} - t_k$, is not constant, however, and depends on the acceleration, i.e., $\alpha_k$, at time $k$. The time interval, i.e., $\Delta t$, is computed by (11) using each interval of distance $\Delta s$ of the original driving cycle. For each $\Delta s$ covered, both initial velocity and initial time are known, and therefore, the time $\Delta t$ to travel distance $\Delta s$ is computed by (11). The optimal speed profile, i.e., $v^*(t)$, is derived at each time through the following equation:

$$v_{k+1}^* = \sum_{k=0}^{n} \left( v_k^* + a_k^* \cdot (t_{k+1} - t_k) \right). \tag{12}$$

This process was repeated over all of the distance intervals, and the new velocity and time vectors were constructed.

## B. Optimized Driving Cycles

The optimization framework previously described was applied to three driving cycles: Japan 10-15, combined FTP and HWFET, and FTP. In the case of the combined FTP and HWFET driving cycles, a new optimized driving cycle was obtained, as shown in Fig. 10. The optimal driving cycle is 3.5 min longer than the original driving cycle since the new acceleration profile aims to smooth out the vehicle speed. The speeds for both the original and optimized driving cycles versus distance are shown in Fig. 11. Although the optimized speed profile in some instances falls slightly below the bound of the speed profile, which is 5 km/h less than the original cycle, the

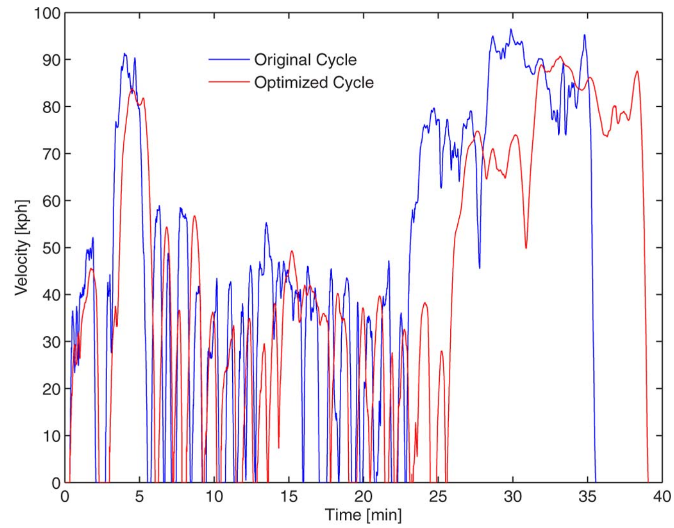


Fig. 10. Optimized vehicle speed profile of combined FTP and HWFET driving cycles with respect to time.

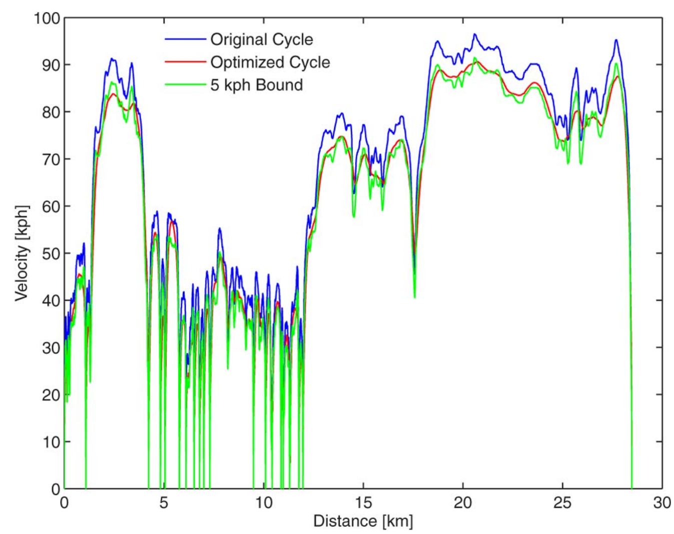


Fig. 11. Optimized vehicle speed profile of combined FTP and HWFET driving cycles with respect to distance.

optimal solution is bounded by the active constraint in (9). For the optimized cycle, it should be noted that the total distance traveled and intermediate stops have been preserved (i.e., the route has been preserved).

A number of concrete conclusions emerged from applying the proposed optimization framework. Smoothing out the speed profile to eliminate transient engine operation results in significant fuel economy enhancement, as shown in Fig. 12. A more conservative driving style that delays destination arrival time by 3.5 min has a major impact on fuel consumption; in this particular case, a 15.9% improvement was observed. Similar qualitative results were observed for the Japan 10-15 and FTP driving cycles. However, delaying the destination arrival time by 3.5 min might not be acceptable to all drivers. Thus, using the optimization problem formulation in (10), we can customize the acceptable additional destination time and limit our feasible optimal solution space. Fig. 13 shows the optimized combined FTP and HWFET driving cycles when the constraint limits the

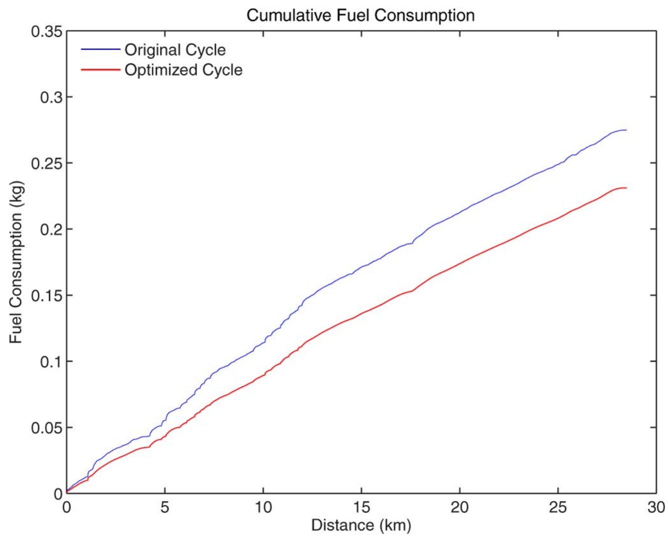


Fig. 12. Cumulative fuel consumption of the original and optimized combined FTP and HWFET driving cycles.

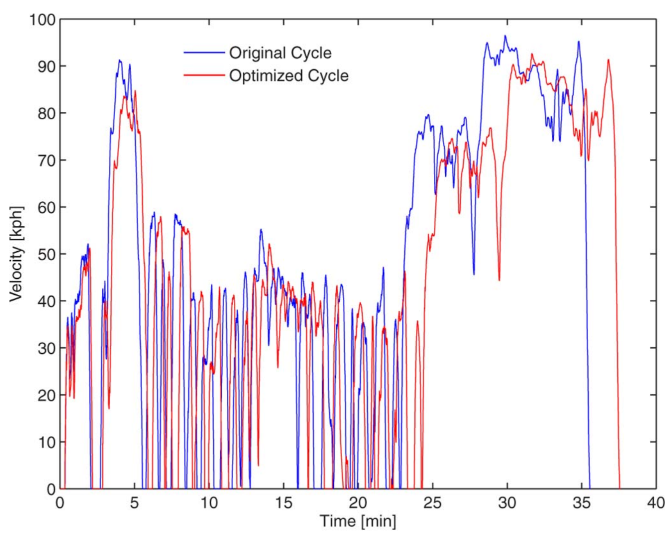


Fig. 13. Optimized vehicle speed profile of combined FTP and HWFET driving cycles with respect to time when a 5% time constraint is imposed.

TABLE II
SUMMARY OF OPTIMIZATION RESULTS

| DRIVING CYCLE | ADDITIONAL TRAVEL TIME (%) | FUEL CONSUMPTION IMPROVEMENT (%) |
|---|---|---|
| JAPAN 10-15 | 28.0 | 22.3 |
| COMBINED FTP AND HWFET | 9.8 | 15.9 |
| FTP | 14.1 | 23.2 |

additional travel time to no more than 5% of the original travel time. Table II summarizes the improvement in fuel consumption for the three driving cycles when the optimization problem in (9) is used. Table III summarizes the improvement in fuel consumption for the optimization problem formulation in (10), in which the additional travel time is constrained to within 5%.

We could modify the optimization problem by trying to maintain the same average speed for both the original and

TABLE III
SUMMARY OF OPTIMIZATION RESULTS WITH TIME CONSTRAINT

| DRIVING CYCLE | ADDITIONAL TRAVEL TIME (%) | FUEL CONSUMPTION IMPROVEMENT (%) |
|---|---|---|
| JAPAN 10-15 | 4.6 | 9.6 |
| COMBINED FTP AND HWFET | 5.0 | 4.6 |
| FTP | 5.0 | 4.5 |

the resulting driving cycles. However, in this problem, the original driving cycle is assumed to be the speed limit, which cannot be exceeded by the resulting driving cycle. Moreover, in this case, we would overconstrain the problem, with the result that no feasible solution could be derived, unless the constraints initially imposed to preserve the distance (i.e., the route) were relaxed. In this formulation, however, the optimized driving cycle would just imply a change in the route. In this paper, we were interested in preserving the original route (e.g., traffic lights and stop signs) and investigating the impact of the coefficient of power demand on fuel economy.

## *C. Driver Feedback System*

The optimization framework previously presented can be used to develop a real-time feedback system with visual instructions to enable drivers to alter their driving styles in response to actual driving conditions to improve fuel efficiency. Such an approach would work as follows. First, the driver has to drive the desired route using his/her typical style. A flash drive plugged into the onboard diagnostics of the engine records two required signals: 1) the vehicle speed profile and 2) the fuel consumption rate. After completing the trip, the driver downloads these two signals in an application running the optimization framework previously presented. The user can select the criteria for optimizing his/her driving style in the optimization problem; for example, an optimized driving style should vary no more than a certain number of kilometers per hour from the original driving cycle [optimization problem (9)], or the arrival time should not exceed a certain percentage of the original time [optimization problem (10)].

After running the application, the new optimized vehicle speed profile can be used by the driver to learn how to adapt his/her driving style to the optimized driving cycle as follows. The optimal acceleration profile is integrated over the time intervals and then multiplied by a time-varying coefficient $c_1(t)$. Thus

$$c_1(k) \cdot \left(a^*_{k+1} - a^*_k\right) \cdot (t_{k+1} - t_k) = 1, \quad k = 1, 2, \ldots, n, n \in \aleph \tag{13}$$

where $n$ is the time horizon of the driver's route. Coefficient $c_1(t)$ makes this product at each time interval $\Delta t$ always equal to 1. This can be represented as the area of a square, as shown in Fig. 14. We define another time-varying coefficient, i.e., $c_2(t)$, that multiplies the current acceleration profile created as the driver drives the vehicle. Thus

$$c_2(k) \cdot (a_{k+1} - a_k) \cdot (t_{k+1} - t_k) = \frac{1}{c_1(k)}. \tag{14}$$

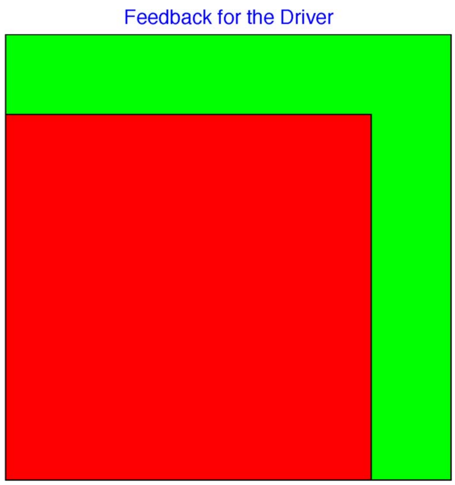


Fig. 14. Visual instruction area corresponding to (in green) the optimal acceleration profile and (in red) the driver's acceleration profile as he/she is operating the vehicle.

Coefficient $c_2(t)$ makes the product on the left-hand side of (14) less than 1 at each time interval $\Delta t$ as long as the driver's acceleration $\alpha(t)$ at each time interval $\Delta t$ is less than optimal acceleration profile $\alpha^*(t)$. This product represents the area of another square shown in red in Fig. 14. Coefficient $c_2(t)$ is computed at each instant of time from (14) based on the driver's acceleration, and the corresponding (red square) is plotted against the area of the optimal acceleration profile. Hence, the green rectangle is constant and represents instantaneous optimal acceleration. The red rectangle represents the driver's instantaneous acceleration and changes over time with respect to the accelerator pedal position. As the driver drives the vehicle, the instantaneous acceleration (red square) should be less than or just overlap the optimal acceleration profile (green square) at each instant of time. The belief implicit here is that after repeating the same route by following these visual instructions, the driver will eventually learn the optimized driving style. Thus, eventually, the driver will learn the most efficient position of the accelerator pedal to achieve a certain amount of benefit in fuel economy.

## V. Conclusion

In the research reported here, we identified and justified the key driving factors that can provide an efficient indication of idle and transient engine operation deemed characteristic of high fuel consumption. We then constructed a set of polynomial metamodels that reflected the responses produced in fuel consumption by changes in these driving factors. Finally, we developed an optimization framework that can be used to optimize a driving style based on a driver's needs and preferences. The solution of the optimization problem confirmed that smoothing out the speed profile to eliminate transient engine operation results in significant fuel economy enhancement. For instance, we showed that a more conservative driving style that delayed destination arrival time by 3.5 min has a major impact on fuel consumption in the combined FTP and HWFET driving cycles. However, for cases where delaying destination arrival might not be acceptable for a driver, we formulated an alternative optimization problem in which we can customize the acceptable additional destination time. We used this framework to develop a driver feedback system that can provide visual instructions to the driver to alter his/her driving behavior.

Individual driving styles vary and rarely meet the driving conditions posited in testing (e.g., engine optimization with respect to steady-state operating points or vehicle speed profiles for particular highway and city driving). The optimization framework developed here facilitates better understanding of the potential benefits from using a more conservative driving style. Although more conservative driving may delay destination arrival time, its impact on fuel economy is substantial.

The variation in fuel consumption for different driving styles is significant; hence, developing a means for improving driver behavior to maximize fuel economy is a significant opportunity to reduce fuel consumption in existing fleets. The long-term potential benefits of this driver feedback system are substantial. Drivers will be able to evaluate their driving behavior and learn how to improve their driving styles based on their own preferences. Realizing a more eco-friendly driving style can significantly contribute to sustainable mobility. It is acknowledged, however, that there are constraints that will dictate the overall fuel efficiency, e.g., traffic; furthermore, an eco-driving style may cause congestion. Future research should address the potential of creating driver feedback systems that will take into account traffic information with the aim of reducing the impact on these aspects.

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